# **Measures everywhere**

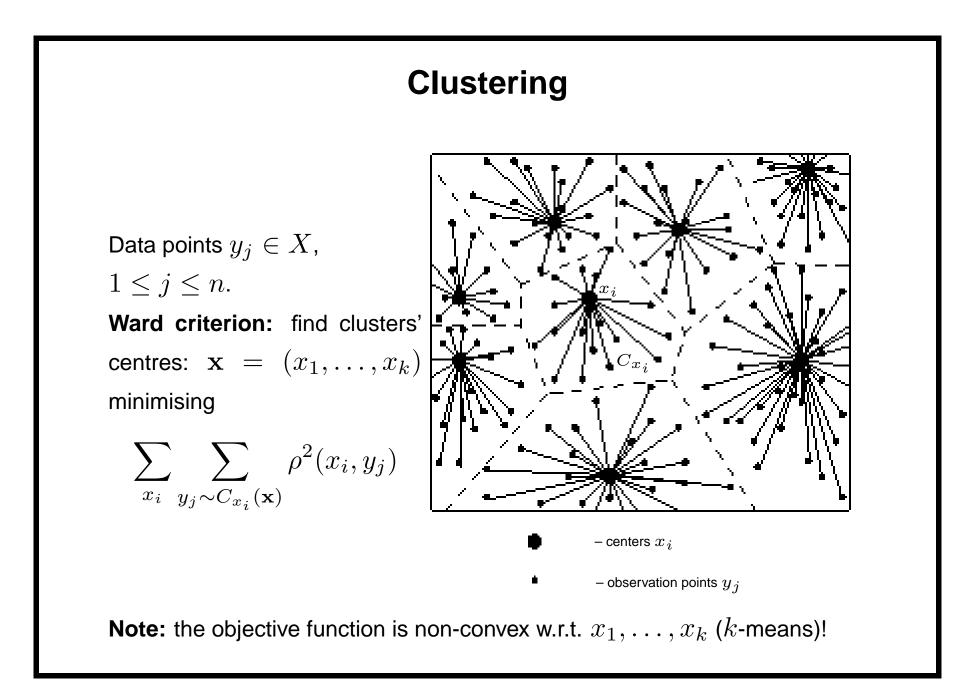
Applications

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# **Applications already considered**

- Estimation of mixture distribution
- Generalisations of Kiefer-Wolfowitz theorem in optimal design
- Russo's Formula and Gamma-type results in stochastic geometry
- Numeric integration of functions and Approximation of convex bodies

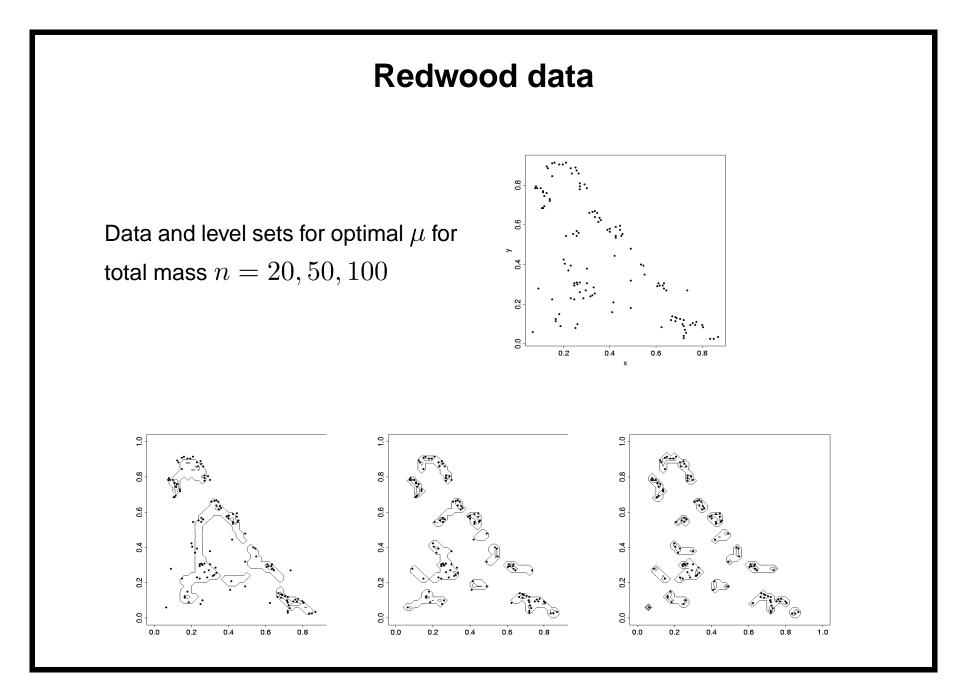


#### Poissonisation

**Cluster centres:** Poisson process  $\Pi_{\mu}$  with intensity  $\mu$  with  $\mu(X) = k$ 

$$\mathbf{E}_{\mu} \left[ \sum_{x_i \in \Pi_{\mu}} \sum_{y_j \sim C_{x_i}(\Pi_{\mu})} \rho^2(x_i, y_j) \right] = \sum_{y_j} \mathbf{E}_{\mu} [\rho^2(y_j, \Pi_{\mu})]$$
$$= \sum_{y_j} \int \exp\{-\mu(b_{\sqrt{t}}(y_j) \cap X)\} dt$$

**Note:** The objective function is strictly convex w.r.t.  $\mu$ !



### **Telecommunications example**

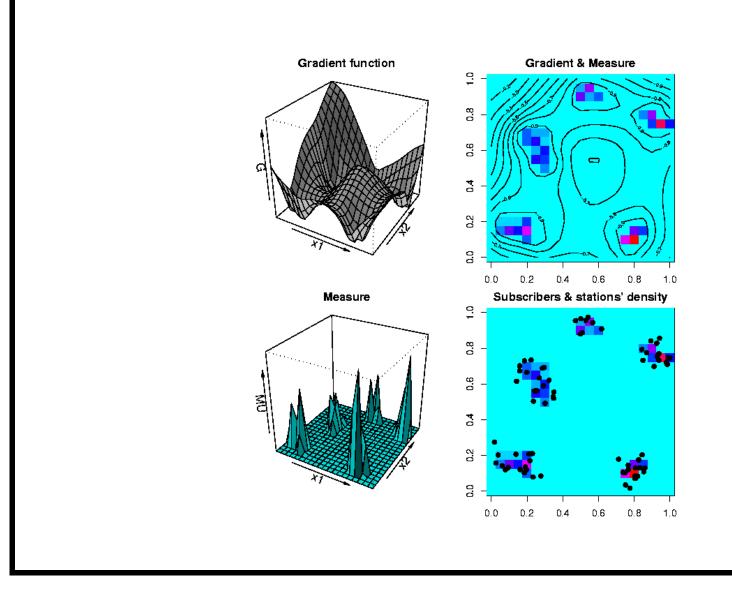
- Daughter points  $\equiv$  subscribers (or demand).
- Cluster centers  $\equiv$  local exchanges (stations)

**Problem:** Find density  $\mu$  of stations minimising the average connections cost of subscribers to the stations:

$$\mathbf{E}_{\mu} \sum_{x_i} \sum_{y_j \sim C_{x_i}(\Pi)} \rho^{\beta}(x_i, y_j) \,.$$

 $\Box$  High intensity solution: Density of stations  $p_{\mu}(x) \propto q(x)^{d/(d+\beta)}$ , where q is the density of the demand (d = 2 typically)

# **Optimal placement of stations**

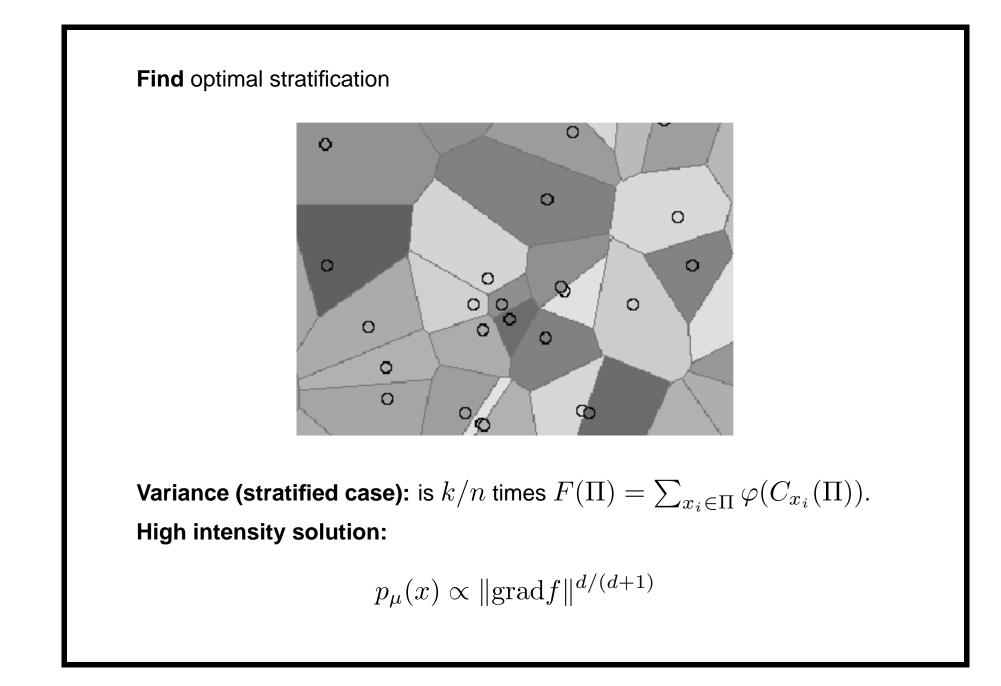


# Monte Carlo integration

Aim: calculate  $\int_X f(y) dy$  ,  $X \subset \mathbb{R}^d$ 

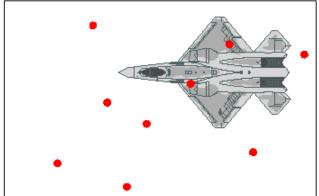
$$\begin{split} \int_X f(y) dy &\approx [f(U_1) + \dots + f(U_n)]/n = I_n \,, \\ \mathrm{Var} I_n &= \frac{1}{n} \varphi(X) \\ \mathrm{where} \; \varphi(X) &= \ell(X) \int_X f(y)^2 dy - \left[ \int_X f(y) \, dy \right]^2 \end{split}$$

**Stratification:** split X into k sub-regions and sample n/k points from every sub-region



# **Optimal random search**

(How to catch a random set using Poisson traps?)



- $Y \subset X$  is a random closed set indepentednt of  $\Pi$ .
- Maximise trapping probability  $\mathbf{P}_{\mu}\{Y \cap \Pi \neq \emptyset\}$

• 
$$\overline{\Delta}_{\mu}(x) = \mathbf{E}_{\mu}[e^{-\mu(Y)} 1\!\!1_{x \in Y}]$$

**Example:**  $X = \{0, 1, 2, ...\}$ 

 $Y = \{\xi\}$  geometrically distributed random singleton:  $\mathbf{P}\{\xi = \{i\}\} = pq^i$ If  $\mu(\{i\}) = m_i$ , then (maximisation!)

$$\overline{\Delta}_{\mu}(x) = e^{-m_i} p q^i \begin{cases} = u & i \in \operatorname{supp} \mu, \\ \leq u & \forall i \end{cases}$$

Thus  $m_i = -\log(u/(pq^i))$  on  $\operatorname{supp} \mu$  and hence  $\operatorname{supp} \mu$  is finite as otherwise  $m_i$  become negative.

**L** E.g., if p = q = 0.5 and  $a = \mu(X) = 1$ , then supp  $\mu = \{0, 1\}$  with  $m_0 = 0.847, m_1 = 0.153$ , trapping probability is 0.3211

Compare:

0.5 = trapping probability using the fixed trap at 0 (not Poisson). But trapping probability given  $\Pi(X) > 0$  is  $0.3211/(1 - e^{-1}) = 0.509$ .

### **Catching a random ball**

 $X \subseteq \mathbb{R}^d$ ,  $Y = b_\rho(\xi)$  random ball of radius  $\rho$  at  $x \in X$  $\xi$  and  $\rho$  are independent and have continuous densities

$$\overline{\Delta}_{ap(x)\lambda}(x) \propto -p_{\xi}(x)b_{d}d^{-1} \\ \times \left[\frac{p_{\rho}(0)(d+1)\Gamma(1+1/d)}{(ap(x)b_{d})^{1+1/d}} + \frac{p_{\rho}'(0)(d+2)\Gamma(1+2/d)}{(ap(x)b_{d})^{1+2/d}} + \cdots\right]$$

#### High intensity solution:

 $p(x) \propto (p_{\xi}(x))^{d/(d+k+1)}$ , where k is the first non-zero  $p_{\rho}^{(k)}(0)$ .

# **Design of materials**

#### **Boolean model:**

$$\Xi = \bigcup_{x_i \in \Pi_\mu} (x_i + \Xi_i)$$

 $\Pi$  Poisson process with intensity measure  $\mu,$ 

 $\Xi_0$  is a typical grain (e.g.,  $b_{\xi}(0)$ ).

Minimise the expected uncovered volume (convex function!):

$$\psi(\mu) = \mathbf{E} \operatorname{Vol}(X \setminus \Xi) = \int_X e^{-\mathbf{E} \,\mu(x - \Xi_0)} dx \mapsto \min$$

Gradient:

$$d(x,\mu) = -\mathbf{E}\left[\int_{\Xi_0+x} e^{-\mathbf{E}\,\mu(y-\Xi_0)}dy\right]$$

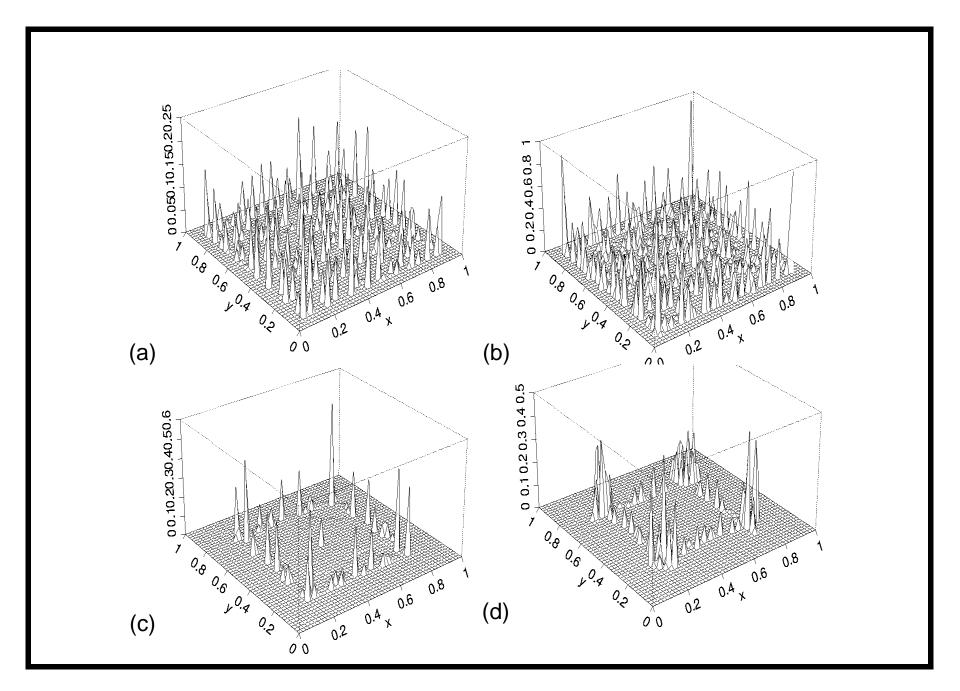
Measures maximising the expected covered area in  $X = [0, 1]^2$  with the fixed total mass a. The typical grain is a ball of radius r.

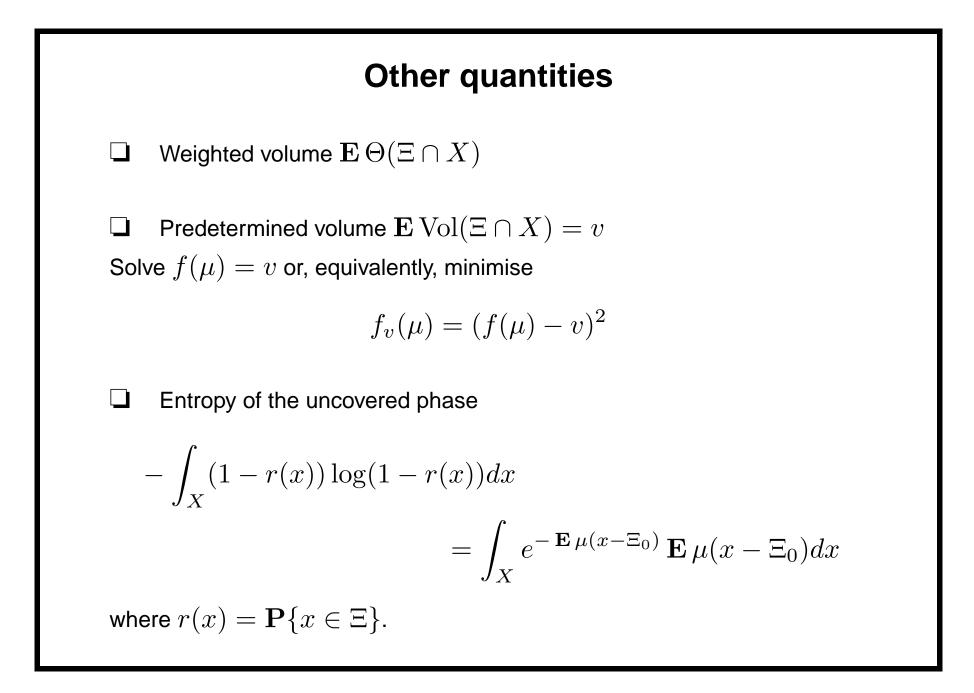
(a) 
$$a = 10, r = 0.1;$$

(b) 
$$a = 50, r = 0.1;$$

(c) a = 10, r is exponentially distributed with mean 0.1;

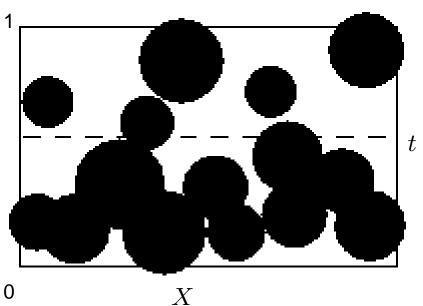
(d) 
$$a = 10, r = 0.3$$
.





# **Functionally graded materials (FGM)**

 $\Xi$  is a Boolean model in  $X \times [0, 1]$ . The last coordinate (height) is used for grading



Expected uncovered volume at height t is called density profile

$$q(t,\mu) = \mathbf{E}_{\mu} \operatorname{Vol}(\Xi^{c} \cap (X \times \{t\}))$$
$$= \int_{X} \exp\{-\mathbf{E} \,\mu((x,t) - \Xi_{0})\} dx.$$

### **Design of FGM**

Assume:  $\mu = dx \times \nu(dt)$  is homogeneous on X and  $\Xi_0 = B_{\xi}(0)$ Aim: Given h(t), design FGM (measure  $\mu$ ) such that

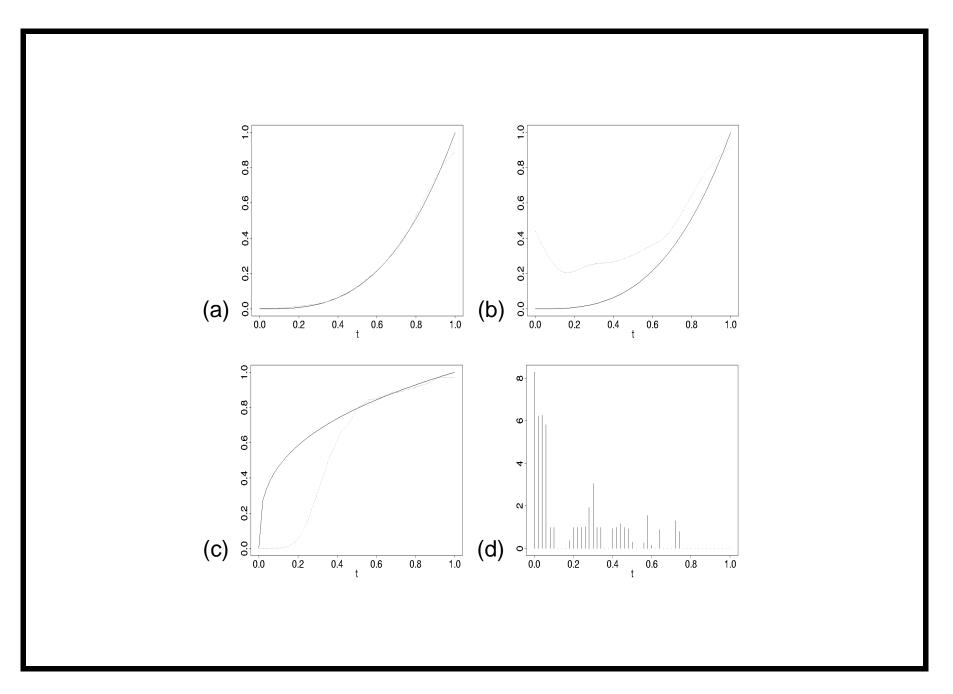
$$q(t,\mu)=h(t), \ t\in [0,1]$$
 or 
$$\psi(\mu)=\int_0^1(q(t,\mu)-h(t))^2\nu(dt)\mapsto\min$$

$$q(t,\mu) = \exp\left\{-\int_0^1 g(s,t)\nu(ds)\right\}$$
$$g(s,t) = b_d \mathbf{E}\left[\max(\xi^2 - (s-t)^2, 0)^{d/2}\right]$$

Target density profiles h (solid lines) and the calculated density profiles  $q(t, \Lambda)$  (dashed lines) for optimal measures with a total mass 50. (a) d = 1,  $h(t) = t^3$ ; (b) d = 2,  $h(t) = t^3$ ;

(c) 
$$d = 1$$
,  $h(t) = t^{1/3}$ ;

(d) The optimal  $\nu$  for the case (a).



Some subjects non-covered in the course
Infinite mass measures
Second order necessary conditions for $\inf$
Specific constraints, e.g. class of absolutely continuous measures
P-design measures
Sequential Gamma-type results
Hitting properties of stopping sets
Projected gradient descent
Other applications

# References

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- I. Molchanov and S. Zuyev. Steepest descent algorithms in space of measures. Statistics and Computing, 12, 2002, 115–123.
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- M. van Lieshout, I. Molchanov and S. Zuyev. Clustering methods based on variational analysis in the space of measures. Biometrika, **88**, 2001, 1021–1033.

